A Multi-Objective Approach Based on TOPSIS to Solve the Image Segmentation Combination Problem

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Proposed Approach

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Image segmentation

Definition :

Aims to represent the image content into different regions of coherent properties with homogeneous characteristics (such as texture)



Image segmentation

Definition :

Aims to represent the image content into different regions of coherent properties with homogeneous characteristics (such as texture, color,)



Image segmentation

Definition :

Aims to represent the image content into different regions of coherent properties with homogeneous characteristics (such as texture, color movement,...)





Definition :

- Group of pixels connected to each other with similar properties
- Set of pixels that belong to the same class





Ill-posed problem :

- Large number of possible partitioning solutions for any image
- What segmentation criterion can be used?

 $\rightarrow\,$ Choosing the most appropriate criterion able to generate the best segmentation result

Principal approaches

- Contour approach
- Region approach
- Hybrid approach

Other approach

Fusion approach :

- Combining multiple segmentation maps of the same image according to certain criteria
- \rightarrow Goal : providing a final improved segmentation result

Other approach

Fusion segmentation methods :

- Cluster variance [Mignotte 2008]
- Maximum-margin hyperplane [Ceamanos et al 2010]
- Probablistic Rand Index (PRI) [Mignotte 2010]
- Variation of Information (VoI) [Mignotte 2014]
- Precision-Recall (F-measure) [Hélou and Mignotte 2014]
- Weights of evidence model [Song and Li 2014]
- …

A Multi-Objective Approach Based on TOPSIS Results

Proposed approach

• Fusion of segmentations based on multi-objective optimization

A Multi-Objective Approach Based on TOPSIS Results

Fusion segmentation model



$\{S_k\}_{k\leq L}=\{S_1,S_2,\ldots,S_L\}$: a set of segmentations



Final segmentation

A Multi-Objective Approach Based on TOPSIS Results

Segmentation ensemble generation

 The initial segmentations are simply acquired by a clustering algorithm :K-means







http://de.wikipedia.org/wiki/K-Means-Algorithmus

A Multi-Objective Approach Based on TOPSIS Results

Segmentation ensemble generation

• The initial segmentations are simply acquired by a clustering algorithm : K-means



http://de.wikipedia.org/wiki/K-Means-Algorithmus

• With 12 different color spaces, namely; RGB, HSV, YIQ, XYZ, LAB, LUV, I123, H123, YCbCr, TSL, HSL, P1P2



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Segmentation ensemble generation



local histogram is re-quantized, for each color channels, in a $N_b = q^3$ bin descriptor (q = 5, estimated on an overlapping, squared fixed-size ($N_w = 7$) neighborhood

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A Multi-Objective Approach Based on TOPSIS Results

Multi-objective optimization

Definition :

 $\begin{array}{ll} minimize & \overrightarrow{f}(\overrightarrow{x}) & (k \ fonctions \ to \ be \ optimized) \end{array} (1) \\ with & \overrightarrow{g}(\overrightarrow{x}) & (m \ inequality \ constraints) \\ and & \overrightarrow{h}(\overrightarrow{x}) & (p \ equality \ constraints) \\ where & \overrightarrow{x} \in \Re^n, \ \overrightarrow{f}(\overrightarrow{x}) \in \Re^k, \ \overrightarrow{g}(\overrightarrow{x}) \in \Re^m, \ \overrightarrow{h}(\overrightarrow{x}) \in \Re^p \end{array}$

A Multi-Objective Approach Based on TOPSIS Results

Multi-objective optimization

Resolution methods :

• A priori preference method

Assign a numerical weight to each objective and combining its multiple objectives by adding all weighted criteria into a single composite function

• Progressive preference technique

User refines his choice of the compromise during the progress of the optimization

• Posteriori preference method

Define a dominance relationship, where the overarching goal is to find the best compromise between objectives

[Collette and Siarry 2004]

A Multi-Objective Approach Based on TOPSIS Results

Multi-objective optimization

Resolution methods :

- A priori preference method
- Progressive preference technique
- Posteriori preference method

[Collette and Siarry 2004]

A Multi-Objective Approach Based on TOPSIS Results

Multi-objective optimization

Definition (Pareto dominance) :

The solution $x^{(i)} \in S$ dominates another solution $x^{(j)} \in S$, denoted $x^{(i)} \prec x^{(j)}$ (in the case of minimization), if and only if :

•
$$\forall \ l \in \{1, 2, .., k\} \mid f_l(x^{(i)}) \le f_l(x^{(j)})$$

• $\exists l \in \{1, 2, .., k\} \mid f_l(x^{(i)}) < f_l(x^{(j)})$

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Multi-objective optimization



- Pareto frontier of a multi-objective problem in case of a minimization-

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Proposed Approach

• Hybrid approach : region + contour \rightarrow GCE+F-measure

A Multi-Objective Approach Based on TOPSIS Results

GCE criterion (global consistency error)

Definition :

- computes the coherence between two or more segmentations
- A perfect correspondence is obtained if each region in one of the segmentation is a subset or geometrically similar to a region in the other segmentation

[Martin et al 2001]

A Multi-Objective Approach Based on TOPSIS Results

(2)

GCE criterion (global consistency error)

LRE (local refinement error) at pixel p_i :

$$\mathsf{LRE}(S^{\mathsf{t}}, S^{\mathsf{g}}, p_i) = \frac{|C^{\mathsf{t}}_{< p_i >} \backslash C^{\mathsf{g}}_{< p_i >}|}{|C^{\mathsf{t}}_{< p_i >}|}$$

with

$$\begin{split} S^{\mathsf{t}} &= \{C_1^{\mathsf{t}}, C_2^{\mathsf{t}}, \dots, C_{R^{\mathsf{t}}}^{\mathsf{t}}\}: \text{segmentation} \\ S^{\mathsf{g}} &= \{C_1^{\mathsf{g}}, C_2^{\mathsf{g}}, \dots, C_{R^{\mathsf{g}}}^{\mathsf{g}}\}: \text{segmentation} \\ R^{\mathsf{t}}: \text{number of region in } S^{\mathsf{t}} \\ R^{\mathsf{g}}: \text{number of region in } S^{\mathsf{g}} \\ p_i: \text{pixel} \end{split}$$

A Multi-Objective Approach Based on TOPSIS Results

(2)

GCE criterion (global consistency error)

LRE (local refinement error) at pixel p_i :

$$\mathsf{RE}(S^{\mathsf{t}}, S^{\mathsf{g}}, p_i) = \frac{|C^{\mathsf{t}}_{\langle p_i \rangle} \backslash C^{\mathsf{g}}_{\langle p_i \rangle}|}{|C^{\mathsf{t}}_{\langle p_i \rangle}|}$$

with

$$\begin{array}{l} C^{\mathsf{t}}_{< p_i >}: \text{segment in} S^{\mathsf{t}} \text{ including pixel } p_i \\ C^{\mathsf{g}}_{< p_i >}: \text{segment in } S^{\mathsf{g}} \text{ including pixel } p_i \\ \backslash: \text{operator of difference} \\ |C|: \text{cardinality of set of pixels } C \end{array}$$

A Multi-Objective Approach Based on TOPSIS Results

GCE criterion (global consistency error)

• If one segment is a subset of the other,





• If there is no subset relationship,



 \rightarrow LRE \neq 0

[Martin et al 2001]

A Multi-Objective Approach Based on TOPSIS Results

GCE criterion (global consistency error)

GCE (global consistency error) :

$$\mathsf{GCE}^{\star}(S^{\mathsf{t}}, S^{\mathsf{g}}) = \frac{1}{2n} \left\{ \sum_{i=1}^{n} \mathsf{LRE}(S^{\mathsf{t}}, S^{\mathsf{g}}, p_{i}) + \sum_{i=1}^{n} \mathsf{LRE}(S^{\mathsf{g}}, S^{\mathsf{t}}, p_{i}) \right\}$$
(3)

where

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n : number of pixel p_i within the image



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GCE criterion (global consistency error)

Mean GCE :

$$\overline{\mathsf{GCE}^{\star}}\left(S^{\mathsf{t}}, \{S_k^g\}_{k \le L}\right) = \frac{1}{L} \sum_{k=1}^{L} \mathsf{GCE}^{\star}\left(S^{\mathsf{t}}, S_k^g\right) \tag{4}$$

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F-measure criterion

Precision and recall



[http://en.wikipedia.org/wiki/File:Precisionrecall.svg]

A Multi-Objective Approach Based on TOPSIS Results

F-measure criterion

Precision and recall



• Precision (P) : fraction of detections of the true boundaries

• Recall (R) : fraction of true boundaries detected [Mignotte et al 2014]

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F-measure criterion

F-measure :

$$F_{\alpha} = \frac{PR}{\alpha R + (1 - \alpha)P}$$

where

 α : controls a harmony between P and R

[Martin et al 2004]

(5)

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Fusion segmentation model

Model solution :

$$\hat{S}_{\overline{\mathsf{F}}_{\alpha},\overline{\mathsf{GCE}}_{\beta}^{\star}} = \begin{cases} \arg\max_{S\in\mathcal{S}_{n}} \left\{ \frac{1}{L} \sum_{K=1}^{L} w_{k} \overline{\mathsf{F}}_{\alpha} \left(S, \{S_{k}\}_{k\leq L}\right) \right\} \\ \bigcap_{\arg\min_{S\in\mathcal{S}_{n}}} \left\{ \overline{\mathsf{GCE}}^{\star} \left(S, \{S_{k}\}_{k\leq L}\right) + \beta E_{\mathsf{Reg}}(S) \right\} \end{cases}$$
(6)

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Fusion segmentation model :

Coefficient of the weight :

$$w_k = \frac{1}{Z} exp\left(\frac{\overline{\mathsf{F}}_{\alpha=0.5}\left(S, \{S_k\}_{k \le L}\right)}{\ell}\right)$$

where

- Z : normalizing constant ensuring $\sum_K w_k = L$
- ℓ : parameter controlling the decay of the weight

\rightarrow Goal : ensuring the robustness of the model

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Fusion segmentation model

Regularization term

$$E_{\mathsf{Reg}}\left(S = \{C_k\}_{k \le R}\right) = \left|-\sum_{k=1}^{R} \frac{|C_k|}{n} \log \frac{|C_k|}{n} - \overline{\mathcal{R}}\right|$$
(7)

where

 ${\boldsymbol R}$: number of regions in segmentation ${\boldsymbol S}$

 \boldsymbol{n} : number of pixels within the image

 $\left|C_{k}\right|$: number of pixels in the k-th region C_{k} of the segmentation map S

 $\overline{\mathcal{R}}$: mean entropy of the a priori defined acceptable segmentation solutions

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Fusion segmentation model

Regularization term

$$E_{\mathsf{Reg}}\left(S = \{C_k\}_{k \le R}\right) = \left|-\sum_{k=1}^{R} \frac{|C_k|}{n} \log \frac{|C_k|}{n} - \overline{\mathcal{R}}\right|$$
(7)

- If the current segmentation solution has an entropy greater than *R* (under segmentation)
 →Favors merging
- In the opposite case
 - \rightarrow Favors splitting

A Multi-Objective Approach Based on TOPSIS Results

Optimization of the fusion model

Iterative Conditional Modes (ICM) :

Initialization of parameters

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Optimization of the fusion model

Iterative Conditional Modes (ICM) :

Initialization of parameters

Selection of the initial solution (segmentation) $\hat{S}_{GCE_{2}}^{[0]}$

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Optimization of the fusion model

Iterative Conditional Modes (ICM) :

Initialization of parameters Selection of the initial solution (segmentation) $\hat{S}_{GCE_{j}}^{[0]}$ For each b_k superpixel $\in \{S_k\}_{k \leq L}$ do Generate a new segmentation $\hat{S}^{[p],new}$ (draw a new label for b_k) $S = \hat{S}^{[p],new}$ Compute: $\overline{CCE_{j}^{+}}(S, \{S_k\}_{k \leq L})$



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Optimization of the fusion model

Iterative Conditional Modes (ICM) :



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Optimization of the fusion model



-A set of Pareto solutions (non-dominated) -

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A Multi-Objective Approach Based on TOPSIS Results

Decision Making With TOPSIS

TOPSIS :

- TOPSIS (Technique for Order Performance by Similarity to Ideal Solution)
- Based on the selection of the alternative (solution) that is the closest to the ideal solution and the farthest from the negative ideal solution

[Hwang and Youn 1981]



A Multi-Objective Approach Based on TOPSIS Results

Decision Making With TOPSIS

TOPSIS

Construct the decision matrix

 $X_{ij}, i = 1, 2, ..., n j = 1, 2, ..., m.$

-	i∖j	GCE	F-measure
	Sol.1	0.39	0.52
Х	Sol.2	0.33	0.45
	Sol.3	0.25	0.30
	Sol.4	0.20	0.25

A Multi-Objective Approach Based on TOPSIS Results

Decision Making With TOPSIS

- Construct the decision matrix
- 2 Calculate the normalized decision matrix
 - $N_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{m} X_{ij}^2}} \quad i = 1, 2, .., n \ j = 1, 2, .., m$

	i∖j	GCE	F-measure
	Sol.1	0.39/0.60	0.52/0.79
Ν	Sol.2	0.33/0.60	0.45/0.79
	Sol.3	0.25/0.60	0.30/0.79
	Sol.4	0.20/0.60	0.25/0.79

A Multi-Objective Approach Based on TOPSIS Results

Decision Making With TOPSIS

TOPSIS

- Construct the decision matrix
- 2 Calculate the normalized decision matrix
- Salculate the weighted normalized matrix

 $V_{ij} = N_{ij} * W_j \ i = 1, 2, .., n \ j = 1, 2, .., m$

	i∖j	GCE	F-measure
	Sol.1	0.65*(1/2)	0.65*(1/2)
V	Sol.2	0.55*(1/2)	0.56*(1/2)
	Sol.3	0.41*(1/2)	0.37*(1/2)
	Sol.4	0.33*(1/2)	0.31*(1/2)

A Multi-Objective Approach Based on TOPSIS Results

Decision Making With TOPSIS

TOPSIS

- Construct the decision matrix
- ② Calculate the normalized decision matrix
- Solution Calculate the weighted normalized matrix
- Oetermine the ideal solution A^+ and the negative ideal solution A^-

$$A^{+} = \{V_{1}^{+}, V_{2}^{+}, ..., V_{n}^{+}\} \\ = \{(max_{i}V_{ij} \mid j \in J), (min_{i}V_{ij} \mid j \in J')\}$$

$$A^{-} = \{V_{1}^{-}, V_{2}^{-}, .., V_{n}^{-}\} = \{(min_{i}V_{ij} \mid j \in J), (max_{i}V_{ij} \mid j \in J')\}$$

i∖i GCE F-measure Sol.1 0.32 0.32 0.27 Sol.2 0.28 V Sol.3 0.20 0.18 Sol.4 0.16 0.15

A Multi-Objective Approach Based on TOPSIS Results

Decision Making With TOPSIS

- Construct the decision matrix
- ② Calculate the normalized decision matrix
- Solution Calculate the weighted normalized matrix
- Oetermine the ideal solution A^+ and the negative ideal solution A^-
- $\hfill Scale and the separation measure from the ideal solution <math display="inline">(E_i^+)$ and the negative ideal solution (E_i^-)

$$\begin{split} E_i^+ &= \sqrt{\sum_{j=1}^n (v_{ij} - v_j +)^2}; i = 1, 2, .., n\\ E_i^- &= \sqrt{\sum_{j=1}^n (v_{ij} - v_j -)^2}; i = 1, 2, .., n \end{split}$$

i∖j	GCE	F-measure	E+
Sol.1	(0.32-0.16) ²	(0.32-0.32) ²	0.16
Sol.2	(0.27-0.16) ²	(0.28-0.32) ²	0.11
Sol.3	(0.20-0.16) ²	(0.18-0.32) ²	0.14
Sol.4	(0.16-0.16) ²	(0.15-0.32)2	0.17

i∖j	GCE	F-measure	E-
Sol.1	(0.32-0.32) ²	(0.32-0.15) ²	0.17
Sol.2	(0.27-0.32) ²	(0.28-0.15) ²	0.13
Sol.3	(0.20-0.32) ²	(0.18-0.15) ²	0.12
Sol.4	(0.16-0.32) ²	(0.15-0.15) ²	0.16

A Multi-Objective Approach Based on TOPSIS Results

Decision Making With TOPSIS

- Construct the decision matrix
- ② Calculate the normalized decision matrix
- Solution Calculate the weighted normalized matrix
- Oetermine the ideal solution A^+ and the negative ideal solution A^-
- Solution (E_i^+) and the negative ideal solution (E_i^-)
- $\ensuremath{\textcircled{}}$ Calculate the relative closeness $(\overline{C_i^*})$ of each alternative to the ideal solution

$$(\overline{C_i^*}) = \frac{E_i^-}{E_i^+ + E_i^-}; 0 \le \overline{C_i^*} \le 1$$

	C_i^*
Sol.1	0.51
Sol.2	0.54
Sol.3	0.46
Sol.4	0.48

A Multi-Objective Approach Based on TOPSIS Results

Decision Making With TOPSIS

- Construct the decision matrix
- 2 Calculate the normalized decision matrix
- Solution Calculate the weighted normalized matrix
- Oetermine the ideal solution A⁺ and the negative ideal solution A⁻
- Solution (E_i^+) and the negative ideal solution (E_i^-)
- 0 Calculate the relative closeness $(\overline{C_i^*})$ of each alternative to the ideal solution
- O Choose an alternative with maximum of $(\overline{C_i^*})$

	C_i^*
Sol.1	0.51
Sol.2	0.54
Sol.3	0.46
Sol.4	0.48

A Multi-Objective Approach Based on TOPSIS Results

Berkeley Segmentation Dataset

Berkeley Segmentation Dataset (BSD300) :

- test set of 100 images.
- training set of 200 images
- 5 manually segmentations per image



A Multi-Objective Approach Based on TOPSIS Results

Evaluation of the Performance

PRI (Probabilistic Rand index) :

Counts the fraction of pairs of pixels whose labels are consistent between the computed segmentation and the human segmentation, averaging through all ground truth segmentation of a given image

	BSDS300		
	VoI	GCE	PRI
-HUMANS-	1,10	0,08	0,87
-MOBFM-	1.98	$0,\!20$	0,80
-GCEBFM-	2,10	0,19	0.80
-FMBFM-	2,01	0,20	0.80
-VOIBFM-	1,88	0,20	0.81
-PRIF-	$1,\!97$	0,21	0.80
-FCR-	$2,\!30$	0,21	0.79
-CTM-	2,02	0,19	0.76
-CRKM-	$2,\!35$	-	0.75
-Mean-Shift-	2,48	0,26	0.75
-FH-	$2,\!66$	0,19	0.78
-DGA-AMS-	2,03	-	0.79
-LSI-	-	-	0.80

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A Multi-Objective Approach Based on TOPSIS Results

Evaluation of the Performance

PRI (Probabilistic Rand index) :

 $PRI = 0.80 \rightarrow on average, 80 \%$ of pairs of pixel labels are correctly labeled (on average) in the results of segmentation on the BSD300.

	I	BSDS300		
	VoI	GCE	PRI	
-HUMANS-	1,10	0,08	0,87	
-MOBFM-	1.98	0,20	0,80	
-GCEBFM-	2,10	0,19	0.80	
-FMBFM-	2,01	0,20	0.80	
-VOIBFM-	1,88	0,20	0.81	
-PRIF-	$1,\!97$	0,21	0.80	
-FCR-	$2,\!30$	0,21	0.79	
-CTM-	2,02	0,19	0.76	
-CRKM-	$2,\!35$	-	0.75	
-Mean-Shift-	2,48	0,26	0.75	
-FH-	2,66	0,19	0.78	
-DGA-AMS-	2,03	-	0.79	
-LSI-	-	-	0.80	

A Multi-Objective Approach Based on TOPSIS Results

Evaluation of the Performance

Vol (Variation of Information) :

Measures the amount of information that is lost or gained while switching from one region to another

	BSDS300		
	VoI	GCE	PRI
-HUMANS-	$1,\!10$	0,08	0,87
-MOBFM-	1.98	0,20	0,80
-GCEBFM-	$2,\!10$	0,19	0.80
-FMBFM-	2,01	0,20	0.80
-VOIBFM-	1,88	0,20	0.81
-PRIF-	$1,\!97$	0,21	0.80
-FCR-	$2,\!30$	0,21	0.79
-CTM-	2,02	0,19	0.76
-CRKM-	$2,\!35$	-	0.75
-Mean-Shift-	$2,\!48$	0,26	0.75
-FH-	$2,\!66$	0,19	0.78
-DGA-AMS-	2,03	-	0.79
-LSI-	-	-	0.80

A Multi-Objective Approach Based on TOPSIS Results

Evaluation of the Performance

GCE	(global	consistency error):
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Computes the coherence between two or more segmentations

	I	BSDS300		
	VoI	GCE	PRI	
-HUMANS-	1,10	$0,\!08$	0,87	
-MOBFM-	1.98	0,20	0,80	
-GCEBFM-	2,10	$0,\!19$	0.80	
-FMBFM-	2,01	$0,\!20$	0.80	
-VOIBFM-	1,88	$0,\!20$	0.81	
-PRIF-	1,97	$0,\!21$	0.80	
-FCR-	2,30	$0,\!21$	0.79	
-CTM-	2,02	$0,\!19$	0.76	
-CRKM-	$2,\!35$	-	0.75	
-Mean-Shift-	2,48	$0,\!26$	0.75	
-FH-	2,66	$0,\!19$	0.78	
-DGA-AMS-	2,03	-	0.79	
-LSI-	-	-	0.80	

A Multi-Objective Approach Based on TOPSIS Results

Evaluation of the Performance

BDE (Bondry Displacement Error) :

Measures the average displacement error of boundary pixels between two segmented images

	BSDS300		
	BDE	F-measure	
-HUMANS-	4,99	0.79	
-MOBFM-	8,25	0.59	
-GCEBFM-	8,73	-	
-FMBFM-	8,49	$0,\!62$	
-VOIBFM-	9,30	-	
-PRIF-	8,45	0.64	
-FCR-	8,99	0.56	
-CTM-	9,90	0.58	
-Mean-Shift-	9,70	0.63	
-FH-	9,95	0.58	

A Multi-Objective Approach Based on TOPSIS Results

Evaluation of the Performance

		BSDS300	
		BDE	F-measure
	-HUMANS-	4,99	0.79
	-MOBFM-	8,25	0.59
	-GCEBFM-	8,73	-
F-measure :	-FMBFM-	8,49	0,62
The harmonic mean of precision and	-VOIBFM-	9,30	-
recall	-PRIF-	8,45	0.64
	-FCR-	8,99	0.56
	-CTM-	9,90	0.58
	-Mean-Shift-	9,70	0.63
	-FH-	9.95	0.58

0.58

9,95

A Multi-Objective Approach Based on TOPSIS Results

Evaluation of the Performance



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A Multi-Objective Approach Based on TOPSIS Results

Evaluation of the Performance



-Example of fusion results using respectively $L=5,10,15,20,25,30,35,40,45,50,55,60 \ {\rm input\ segmentations}-$

A Multi-Objective Approach Based on TOPSIS Results

Qualitative results



Images

FCR

GCEBFM

MOBFM



- New fusion model based on multi-objective optimization (MOBFM)
- Using two complementary (edge and region) criteria of segmentation (F-measure and GCE)
- To optimize our fusion model we used a modified ICM algorithm fellowed by a decision making technique (TOPSIS)

Thank you!